Local field potentials allow accurate decoding of muscle activity

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Author contributions: Designed experiments: MWS, LEM, ERO, CE. Collected data: RDF, CE, ERO. Analyzed data: RDF, LEM, MWS. Wrote the paper: RDF, LEM, MWS.
Abstract

Local field potentials (LFPs) in primary motor cortex include significant information about reach target location and upper limb movement kinematics. Some evidence suggests that they may be a more robust, longer-lasting signal than action potentials (spikes). Here we assess whether LFPs can also be used to decode upper limb muscle activity, a complex movement-related signal. We record electromyograms (EMGs) from both proximal and distal upper limb muscles from monkeys performing a variety of reach-to-grasp and isometric wrist force tasks. We show that LFPs can be used to decode activity from both proximal and distal muscles with performance rivaling that of spikes. Thus, motor cortical LFPs include information about more aspects of movement than has been previously demonstrated. This provides further evidence suggesting that LFPs could provide a highly-informative, long-lasting signal source for neural prostheses.

Keywords: EMGs, brain-machine interfaces, action potentials, motor cortex, electrophysiology

Introduction

Action potentials from neurons in the primary motor cortex (M1) have been shown to correlate with both kinematic (Georgopoulos et al. 1982) and kinetic (Evarts 1968) movement parameters. In addition to providing insight into the neural control of movement, these correlations can be exploited to allow users to control brain-machine interfaces (BMIs). Kinematic BMIs based on spike decoders have allowed users to control a cursor (Carmena et al. 2003; Hochberg et al. 2006; Serruya et al. 2002; Taylor et al. 2002) or a robotic arm (Velliste et al. 2008). Alternatively, BMIs using electromyograms (EMGs) decoded from spikes offer the
an exciting possibility to restore natural movement by activating paralyzed muscles via functional
electrical stimulation (FES; Oby et al. 2010; Pohlmeyer et al. 2009).

Spikes can be difficult to record for the decades-long durations necessary for clinically-
viable BMI applications. Chronically-implanted multielectrode arrays typically lose the ability
to record spikes on most of their electrodes after several years (Krüger et al. 2010; Simeral et al.
2011). Thus, the feasibility of using spikes to control a BMI for decade-long periods is uncertain.

LFPs from M1 also convey information about movement (Heldman et al. 2006; Murthy and Fetz
1996; Sanes and Donoghue 1993), and potentially could offer greater recording longevity than
spikes, since they represent the combined activity of thousands of neurons (Andersen et al. 2004)
and thus loss of activity from a few neurons will likely not cause an appreciable change.

Therefore, LFPs offer an intriguing signal for complementing or perhaps replacing spikes as
inputs to BMIs.

LFPs from M1 have been used to decode reach and grasp kinematics (Bansal et al. 2011a;
Bansal et al. 2011b; Mehring et al. 2003; Slutzky et al. 2010; Zhuang et al. 2010) and grasp type
(Stark and Abeles 2007), often with an accuracy comparable to that using spikes (Mehring et al.
2003; Slutzky et al. 2010). However, LFPs have not been used to predict muscle activity. In this
study, we used both LFPs and spikes recorded from M1 to decode the continuous time course of
proximal and distal limb EMGs during both reach-to-grasp and isometric force-production tasks.

A preliminary report of some of these data was published in (Slutzky et al. 2011b).
Methods

All experiments and procedures were approved by the Northwestern University Institutional Animal Care and Use Committee. Four adult rhesus macaques (C, M, J, and T) were trained to perform the behavioral tasks for a liquid reward.

Behavioral Training

Reach-to-grasp task 1: multi-grasp

Monkeys C and M performed the multi-grasp task, which began from a relaxed position with one hand resting on a touchpad, and the other arm restrained. Monkeys were cued to reach to one of three objects positioned about 35 cm from the touchpad by illumination of an LED on the object and a simultaneous “go” tone. The monkeys executed one of three grasps (palmar, lateral, or precision) depending on the shape of the object. Force feedback, measured with a force sensitive resistor embedded in each object, was given in the form of a circular cursor displayed on a monitor in front of the monkeys. Cursor movement was proportional to the amount of grasp force applied, and was required to match one of two force targets. Grasp forces of 14 N and 20 N, 8 N and 12 N, and 0.6 and 1 N were required for the palmar, lateral, and pinch grasps, respectively. The grasp type and force target level of each trial was set in a pseudorandom order. Monkeys were required to maintain each grasp force within the target range for 0.5 s to receive a liquid reward. Monkeys had 5 s to achieve success in each trial.

Reach-to-grasp task 2: ball grasp

Monkey J performed the ball grasp task with one arm, and the contralateral arm restrained. The monkey was required to pick up a ball from a small tray and place it in a plastic tube with a 60-mm opening. The balls were of a variety of diameters and masses: 40 mm, 130 g;
40 mm, 95 g; and 24 mm, 60 g. The monkey began each trial by placing his hand on a touchpad for at least 0.2 s. A go tone, as well as illumination of an LED on the touchpad, indicated the beginning of a 5-second reach time period, during which the monkey attempted to pick up the ball from the tray. Removing the ball from the tray started another 5-second interval, during which the monkey was required to place the ball in the tube in order to receive a liquid reward.

Isometric wrist force task

Monkey T performed the wrist force task with one arm, with the contralateral arm restrained. The monkey used isometric wrist force (in both the flexion-extension and radial-ulnar deviation axes) to move a computer cursor in a center-out task. The monkey was required to move the cursor from a central target (zero force) to one of eight peripheral targets, which were presented in random order. The monkey had 3 seconds to move the cursor into a target and hold it there for 0.5 s to obtain a liquid reward. The monkey’s upper arm was restrained by a custom-fitted cast which maintained his elbow at a 90-degree angle. Force was measured by a 2-axis strain gauge mounted between casts on the monkey’s hand and forearm. Cursor movement distance was proportional to the measured force along each axis. The targets corresponded to a force of 5N, which was approximately 35-50% of the monkey’s maximum voluntary contraction (MVC).

Electrode implantation

Following behavioral training, we surgically implanted a 96-channel silicon electrode array (Blackrock Microsystems) into the primary motor cortex of each monkey contralateral to the arm used in the behavior. All electrodes were 1.5 mm long. Monkeys were anesthetized
with isoflurane and remifentanil and given postoperative analgesics buprenorphine and
meloxicam for 2 and 4 days, respectively. Monkeys M and C were implanted in arm motor areas
and monkeys J and T in hand motor areas of M1, as determined by stereotaxic coordinate,
cortical topology, and intraoperative electrical stimulation using silver ball electrodes (2-5 mA,
200 μs pulses at 60 Hz). Further surgical details have been described elsewhere (Pohlmeyer et al.
2007b).

**Recording procedures**

Recordings were performed using a Cerebus acquisition system (Blackrock), which
analog band-pass filtered all signals from 0.3 Hz – 7.5 kHz before sampling at 30 kHz. Spikes
were digitally high-pass filtered at 300 Hz and thresholded. Spike waveforms were sorted
manually offline. Both single- and multi-unit spikes were included in the analysis. LFPs were
digitally band-pass filtered from 0.3 to 250 Hz and resampled at 1 kHz (monkeys M, J, and T) or
band-pass filtered from 0.3 to 500 Hz and resampled at 2 kHz (monkey C). Data sampled at 2
kHz were further downsampled to 1 kHz prior to analysis. Each 10-minute recording file
included in this analysis was obtained from a different day.

Electromyogram (EMG) signals were recorded using bipolar electrodes, either on the
skin surface (monkeys M and C) or intramuscularly (monkeys J and T). We band-pass filtered
the EMGs with cutoffs at 5 Hz and 500 Hz, and then sampled at 2 kHz. We then digitally
processed the EMGs as follows: high-pass filtered at 50 Hz, full-wave rectified, then low-pass
filtered at 5 Hz and downsampled to 20 Hz for decoding. We repeated our analysis with a low-
pass filter cutoff of 10 Hz to evaluate whether even higher bandwidth signals could be decoded.
All digital filtering was performed in both the forward and backward directions to avoid introducing phase delays in the output.

**Decoding methods and performance assessment**

We selected 6 spectral features from each field potential signal: the local motor potential (LMP, a sliding window average of the raw LFP, (Mehring et al. 2004; Schalk et al. 2007), and the power in 5 different frequency bands (0-4, 7-20, 70-115, 130-200, and 200-300 Hz). We calculated both the LMP and the spectral power using 256-point windows that overlapped by 206 samples so as to provide one sample every 50 ms. We computed the power in each band by applying a Hanning window followed by a fast Fourier transform to each window. For each frequency band, we normalized the log of this power by subtracting the log of the mean power over the entire file. We chose the 150 features that were individually most strongly correlated with the EMG signal (as determined by the mean of the absolute values of the Pearson correlation coefficients, $|r|$, over all muscles for each file) to use for LFP decoding. This was done to reduce the dimensionality of the feature set from a potential total of up to 576 features (number of LFP channels times 6 features per channel). This feature reduction was performed only on the training, not the testing data. For decoding with spikes, we used spike counts in 50 ms bins for each neuron as features, and included all neurons in the analysis.

We used a Wiener cascade model, which has been described in detail elsewhere (Hunter and Korenberg 1986; Perreault et al. 1999; Pohlmeyer et al. 2007b), to decode the EMG signals. Briefly, we computed a set of causal linear filters of length 10 bins (500 ms) by fitting the input features to the outputs of a set of training data. We used a ridge regression technique (Nemati et al. 2007) to avoid ill-conditioned covariance matrices that otherwise result from the highly
correlated inputs. The output of the Wiener filters was convolved with a static nonlinearity
(Pohlmeyer et al. 2007b) implemented by fitting a second-order polynomial between the linear
filter output and the EMG. This was done in a single iteration between linear and nonlinear
components since, when we performed decoding using a second iteration, we found less than a
2% increase in prediction accuracy. For each file, we trained the Wiener cascade decoder on 9
minutes of data and tested it on the remaining minute. As a measure of performance, we
calculated the mean fractional variance accounted for (VAF) between actual and decoded EMG
over all 10 folds as follows (Fagg et al. 2009):

\[
VAF = 1 - \frac{\sum_{j=1}^{M} \left( p_j - \hat{p}_j \right)^2}{\sum_{j=1}^{M} \left( p_j - \hat{p} \right)^2},
\]

where \( M \) is the total number of samples in each fold, \( p_j \) and \( \hat{p}_j \) are the actual and predicted
samples for the fold, and \( \hat{p} \) is the mean EMG over the fold.

Spectral and temporal information analysis

To determine the relative amount of EMG-related information in each frequency band, we
decoded the EMGs using each frequency band separately. For completeness, we also included
the 20-70 Hz frequency band, although it was not used in the overall ensemble decoding
performance evaluation above. We used all electrodes in each file in this analysis (between 92
and 96 features for the various monkeys). We performed a similar analysis to evaluate
information content as a function of filter lag, by decoding with a single lag ranging from 50 to
500 ms.
Results

We analyzed data from a total of 10 files in 4 rhesus macaques (n=2, 4, 2, and 2 files for monkeys C, M, J, and T, respectively). The mean number of trials per file was 171, 198, and 104 for the multi-grasp, ball-grasp, and isometric wrist force tasks, respectively. We recorded EMGs from 4 proximal arm muscles—biceps (Bi), triceps (Tri), anterior and posterior deltoids (ADel and PDel)—in monkeys C and M during the multi-grasp task (Fig. 1a). We recorded from 8 distal muscles in monkeys J and T during the ball-grasp task and isometric wrist force tasks, respectively (Fig. 1a and 1b): extensor carpi radialis longus and brevis (ECRI and ECRb), extensor carpi ulnaris (ECU), extensor digitorum communis (EDC), flexor carpi radialis and ulnaris (FCR and FCU), flexor digitorum superficialis and profundus (FDS and FDP). We placed two sets of electrodes in each of the digit flexor muscles (corresponding to fingers 2-3 and 4-5). We used at least 100 spike signals (one-half to three-quarters of which were single-unit), and at least 92 LFP signals for decoding (see Table 1). For decoding using LFPs, we chose the top 150 features from a total of 552-576, as described in Methods.

EMG predictions made using LFPs and spikes were very similar, and in most cases, highly accurate, for a wide variety of both proximal (Fig. 2a) and distal (Fig. 2b) muscles. We computed the mean decoding performance for each muscle using either LFPs or spikes (Fig. 3a). In the few cases with poor decoding performance, EMG was only poorly modulated by the behavior (e.g., opponens pollicis in the wrist force task). However, even in these cases, LFP and spike decoding performances were similar (these cases are not shown in Fig. 3a for clarity).

Overall, the mean (± s.d.) VAF across all folds, muscles, and behavioral tasks (28 total muscle-file-task combinations), was 0.64 ± 0.16 for LFP decoding and 0.70 ± 0.14 for spike decoding. A histogram of the pairwise differences in decoding performance between spikes and LFPs (Fig.
3b) shows a small bias of 0.07 ± 0.04 toward better decoding using spikes (p=0.003, paired t-test). Thus, EMG decoding performance using LFPs was only slightly inferior to that using spikes.

To explore the dependence of spike and LFP decoding accuracy on signal bandwidth, we repeated our analysis using an EMG low-pass filter cutoff of 10 Hz instead of 5 Hz which caused decoding performance to decrease by about 10% (Fig. 3c). Importantly, LFP and spike performances decreased by a similar amount, thus leaving their relation largely unaffected.

To understand which LFP frequency bands contained the most EMG-related information, we decoded EMG using each frequency band separately (Fig. 4). The three bands in the high-gamma range (70-300 Hz in this study) contributed more information (overall mean VAF = 0.61 ± 0.15) than the three bands centered at frequencies below 70 Hz (0.28 ± 0.15, p<10^{-10}, paired t-test), with the 130-200 Hz and 200-300 Hz bands contributing the most. This is consistent with prior kinematic decoding results using LFPs. The LMP also had had substantial EMG-related information, slightly more than did the 70-110 Hz band (0.51 ± 0.2 vs. 0.48 ± 0.13, p=0.01).

Intriguingly, the LMP did not decode EMG nearly as well in the isometric case as it did in the movement cases, although the isometric data were from only one monkey, so the effect may be subject-related. The delta band (0-4 Hz) had less information than the LMP (0.35 ± 0.15 vs. 0.51 ± 0.20, p<10^{-10}).

EMG-related information also varied as a function of the time lag between the M1 LFPs (or spikes) and EMGs. We found that the optimal lag for decoding EMGs was at 25±86 ms (the center of the 0-50 ms bin) for LFPs and 2±37 ms for spikes (Fig. 5). These differences were not statistically significant (p=0.17, paired t-test). Time lags in Figure 5 represent the centers of the
bins. Spike times in Figure 5 were shifted by 25 ms and LFP times were shifted by 128 ms (to represent the centers of the 256 ms windows used for Fourier transforms).

Finally, we examined decoding performance as a function of the number of electrodes for both LFPs and spikes, by incrementally adding electrodes and recomputing VAF. For spikes, we incremented by all the units recorded on a given electrode. Electrodes were selected in one of two ways: either by adding the most-informative electrodes first (i.e., those with highest $|r|$ values, the best-electrode method), or in random order. For the random-electrode case, we used the mean of 10 different random electrode sequences. In the best-electrode case, (Fig. 6a), LFPs slightly outperformed spikes when fewer than 14 electrodes were used in decoding (equivalence was defined as the point at which $p$ exceeded 0.05 using a t-test at each number of electrodes). However, in the random-electrode case (Fig. 6b), LFPs substantially outperformed spikes even when up to 36 electrodes were used. In both cases, spikes outperformed LFPs with large numbers of electrodes. This corroborates the finding by Bansal et al. (2011b) that the average LFP had more information than the average spike signal, but the most informative spikes had about as much information as the most informative LFPs.

Discussion

These results clearly demonstrate for the first time that LFP signals recorded from a small area of motor cortex can be used to decode EMGs of multiple muscles from both the proximal and distal arm. Moreover, decoding accuracy was nearly as high as with spike signals. The performance level for both spikes and LFPs was comparable to prior studies that used spikes to decode EMG (Carmena et al. 2003; Oby et al. 2010; Pohlmeyer et al. 2007b). This extends the earlier observations of similar performance of LFPs and spikes that were noted for target
discrimination and kinematic trajectory decoding (Mehring et al. 2003; Slutzky et al. 2010). It also adds to the previous demonstrations of high performance using posterior parietal lobe LFPs to decode saccadic and reach target (Pesaran et al. 2002; Scherberger et al. 2005). Since we did not record kinematic data in this study, it was not possible to determine the difference in bandwidth between EMG and kinematics in this particular task. However, prior studies have shown that muscles and the inertia of the limb act as a low-pass filters (Bawa and Stein 1976; Mannard and Stein 1973), and thus EMG in general will have a higher bandwidth than kinematics.

The high-gamma frequency bands contained the most information about muscle activity. This adds to prior reach direction (Rickert et al. 2005) and trajectory decoding results using LFPs (Stark and Abeles 2007; Zhuang et al. 2010) as well as results using subdural field potentials, or ECoG (Chao et al. 2010). We also found a good deal of information in the LMP, and slightly less in the delta band, observations that are similar to previous human ECoG (Ball et al. 2009; Schalk et al. 2007) and monkey LFP studies (Bansal et al. 2011b; Rickert et al. 2005). It is not clear why LMP and delta band decoding performance differed. It is possible that the removal of phase information from the delta band by the fast Fourier transform may be responsible. Interestingly, the LMP did not perform as well during the isometric task. The reason for this is also unclear, and we do not know if it will be a consistent observation across monkeys. To our knowledge, prior studies have not examined the LMP in isometric tasks. This question may merit further investigation.

The optimal time lag between LFPs and EMG was between 0 and 50 ms, as it was for spikes. This is similar to the peak lag at 50-75 ms for EMG prediction using singly-recorded neurons (Cheney and Fetz 1980; Evarts 1966; Morrow and Miller 2003), and slightly shorter
than the peak around 100 ms for force (Humphrey et al. 1970) and kinematics (Moran and
Schwartz 1999).

The ability to decode the continuous time course of EMG suggests that LFPs could be
used to control FES and reanimate paralyzed upper limb muscles. Implanted clinical FES
systems such as the Freehand (Kilgore et al. 1997) are currently restricted to the use of residual
movement and the activity of muscles in the shoulder or neck to control stimulation. In addition
to adding cognitive burden, these methods limit the number of degrees of freedom that can be
independently controlled, typically constraining the user to a few pre-programmed patterns of
stimulation rather than direct control of individual muscles. A controller based on motor cortical
signals could provide a more natural method and allow individual control of many muscles.

Indeed, this approach has been successfully demonstrated in monkeys paralyzed by temporary
nerve blocks, using spikes to control multi-channel stimulation (Moritz et al. 2008; Oby et al.
2010; Pohlmeyer et al. 2009; Pohlmeyer et al. 2007a).

We have shown previously that LFPs retain the same amount of movement-related
information whether or not spike signals can be recorded from the same electrodes (Slutzky et al.
2011a). This provides evidence that LFPs may have greater longevity than spikes, which has
been widely assumed but not proven (Andersen et al. 2004). The fact that LFPs performed as
well as spikes with lower numbers of electrodes, but were gradually outperformed by spikes as
more electrodes were added is consistent with prior work with LFPs (Bansal et al. 2011b). This
result may reflect higher correlation among LFPs than spikes (Bansal et al. 2011b; Flint et al.
2011), although correlations among LFP channels are lower in high-gamma bands (M. Slutzky,
unpublished data, and Bansal et al, 2011a). Thus, LFPs could provide a high-performance,
complementary or alternative BMI input signal to spikes particularly in the long term after many
spikes have been lost. The low sampling rate requirements, potential for greater longevity, and
rich information content of LFPs make them attractive signal sources for BMIs.

Acknowledgments

This work was supported by NIH grants K08NS060223 and R01NS053603. The authors would
like to thank Nicholas Hatsopoulos and Brian London for surgical assistance, and Eric Lindberg
and Luke Jordan for assistance with behavioral training.

References


Figure Legends

Figure 1. Schematic of recorded limb muscle locations. Both (a) medial and (b) lateral views of the arm are shown.

Figure 2. Examples of decoded limb EMGs. Shown are both (a) distal (monkey J) and (b) proximal (monkey C) EMG signals. Both spikes (red) and LFPs (green) accurately predicted actual EMG activity (blue). Numbers on right represent VAF for the test fold from which the examples were drawn.

Figure 3. Summary of EMG decoding. (a) Box plot summary of performance using spikes (red) and LFPs (green), showing VAF distributions over all data for each monkey. Black dots, medians; solid boxes, inter-quartile ranges; whiskers, overall ranges of non-outlier data. Twenty-two of the 28 EMGs are shown, ordered from proximal to distal. Duplicated and task-irrelevant muscles are not included. Dashed lines separate different muscles, with labels color-coded by monkey. (b) Histogram of pairwise differences (VAF_{LFP} – VAF_{spike}) across all muscles and monkeys. (c) Decoding performance of EMG with low-pass filter cutoffs of 5 Hz (light colors) and 10 Hz (dark colors) for spikes (red) and LFPs (green), averaged over all muscles and monkeys.

Figure 4. Relative information in different LFP frequency bands. Each box represents the decoding performance using either a single frequency band or the LMP, for one muscle over all files. (a) Representative examples of single muscles from monkeys C, M, and T. (b) Examples of
5 muscles from monkey J. Results from other muscles were consistent with these examples. Box symbols are the same as in Figure 2.

**Figure 5.** Decoding performance using single time lags for spikes (red) and LFPs (green). Means (thick lines) and standard deviations (shaded areas) include data from all muscles and monkeys. Positive lags represent neural signals occurring before EMG activity.

**Figure 6.** Effects of number of electrodes on decoding performance. Changes in mean performance as a function of the number of electrodes for spikes (red) and LFPs (green), using (a) the best-electrode selection method, and (b) the random-electrode selection method. Shaded areas around thick lines represent standard errors. For the random-electrode selection method these errors were computed over 10 random sequences.

**Table 1.** Number of units and LFPs used in decoding for each file of each monkey.
Decoding accuracy (VAF)

Monkey: M, C, J, T

Proximal ← Distal

ADel ADel PDel PDel Bi Bi Tri Tri ECRl ECRl ECRl ECRl ECU ECU ECU ECU FCR FCR FCR FCR FCR FCU FCU FCU FCU EDC EDC EDC EDC FDP23 FDP45 FDP23 FDP45

# EMG predictions

VAF difference

LFP 5 10 Hz

Spike 5 10 Hz
<table>
<thead>
<tr>
<th>Monkey</th>
<th>Number of units used</th>
<th>% Single units</th>
<th>Number of LFPs used</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>100, 110, 117, 120</td>
<td>53</td>
<td>95</td>
</tr>
<tr>
<td>C</td>
<td>110, 112</td>
<td>71</td>
<td>92</td>
</tr>
<tr>
<td>J</td>
<td>157, 163</td>
<td>70</td>
<td>94</td>
</tr>
<tr>
<td>T</td>
<td>128, 130</td>
<td>72</td>
<td>96</td>
</tr>
</tbody>
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